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Not 'Islands, Entire of Themselves': Exploring the Spatial Context of City-level Robbery Rates

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Abstract

The current study examines spatial dependence in robbery rates for a sample of 1,056 cities with 25,000 or more residents over the 2000–2003 period. Although commonly considered in some macro-level research, spatial processes have not been examined in relation to city-level variation in robbery. The results of our regression analyses suggest that city robbery rates are not spatially independent. We find that spatial dependence is better accounted for by spatial error models than by spatial lag models. Further exploration of various spatial weights matrices indicates that robbery rates of cities within the same state are related to robbery rates of other cities within the same state, regardless of their proximity. Our analyses illustrate how systematic inquiry into spatial processes can alert researchers to important omitted variable biases and identify intriguing problems for future research.

Keywords

City-level robbery rates; Spatial dependence; Spatial weights; State-level covariates

Introduction

Over the past several decades, criminologists have become increasingly appreciative of the importance of spatial dynamics. Geographic space plays a key role in place-based theories of crime such as routine activities theory (Cohen and Felson 1979; Felson 1998), crime pattern theory (Brantingham and Brantingham 1993; see also Anselin et al. 2000), and "hot spots" theories (Roncek and Meier 1991; Sherman et al. 1989; Sherman and Weisburd 1995). In addition, explicit spatial modeling has been incorporated in research on violent crime for areal units at both the relatively small level of aggregation of census tracts or neighborhoods (Cohen and Tita 1999; Kubrin and Weitzer 2003; Morenoff and Sampson 1997; Morenoff et al. 2001; Rosenfeld et al. 1999) and the larger level of aggregation of counties (Baller et al. 2001; Messner et al. 1999). However, despite the growing interest in spatial analyses in criminology in general, there has been a curious neglect of the possibility of statistically and substantively important spatial dependence in the variation of violent crime rates across *cities*, perhaps because cities are usually geographically separate from, rather than adjacent to, other cities.

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The purpose of this study is to explore the spatial context of variation in violent crime rates for an offense of particular concern in urban areas—robbery—for a large sample of U.S. cities. We begin by estimating a baseline model of the structural covariates of city-level robbery rates and test for spatial autocorrelation, using predictors included in most prior city-level studies of violence such as robbery and homicide. At a minimum, the spatial dependence revealed in our analyses implies that variance estimates are biased, which may in turn lead to faulty inference about the baseline covariates. In addition, if spatial dependence violates the regression assumption that the error of prediction for an observation cannot be predicted by its value on an independent variable, sample estimates of the population regression coefficients will be biased. We then apply spatial econometric strategies to track the source of residual correlation. Our analyses provide examples of the deleterious consequences of these assumption violations in commonly used regression models based on city-level data. More broadly, our analyses illustrate how systematic inquiry into spatial dependence can generate new insights about macro-level variation in violent crime.

Previous Macro-level Research on Robbery

Studies of robbery have been conducted mainly at two levels of analysis. Some have considered small areal units such as neighborhoods (Bursik et al. 1990; Smith et al. 2000). For instance, Bellair (2000) considers the complex influences of informal surveillance on street crimes including robbery. Similarly, McNulty and Holloway (2000) consider the effects of public housing on several crimes including robbery in census block groups in Atlanta.

Most research on robbery, however, has been conducted at the city level and generally falls into two categories.[1] The first considers robbery as an example of a serious crime that is usually compared to other serious crimes such as homicide, rape, aggravated assault, and/or burglary (e.g. Shihadeh and Flynn 1996;Stretesky et al. 2004). This research mainly focuses on large cities (100,000 or more residents) and includes a variety of explanatory factors. In fact, our review of the literature indicates that 33 different variables have been included in at least one city-level study of robbery. Yet, this seemingly bewildering array of variables actually boils down to a relatively standard set of covariates that are included in the majority of studies. Most include indicators of socio-economic disadvantage such as unemployment, poverty, female-headed households, and education levels. Recent studies have typically taken Land et al.'s (1990) advice and use principal components analysis to reduce multicollinearity among these factors by including an index described as resource deprivation or disadvantage (Baumer et al. 1998;Kubrin et al. 2006;Steffensmeier and Haynie 2000;Stretesky et al. 2004). This index generally exhibits a strong, positive relationship with robbery rates.

Numerous other factors have been considered in city-level studies of robbery. Yet, the consistency in the relationship of these variables to robbery varies. For example, some measure of population size or density is frequently included and usually, although not always (cf. Steffensmeier and Haynie 2000), is positively related to robbery rates (e.g. Baumer et al. 1998; MacDonald 2002). Similarly, some measure of family disruption such as divorce is often included. Yet, findings on the effects of divorce on robbery are mixed. Some document a relationship (Baumer et al. 1998; Stretesky et al. 2004), whereas others do not (Baumer 1994; MacDonald 2002).

Most studies include an indicator of region and a measure of age structure. The choice of region to include and the relationship to robbery varies widely. Some studies find that robberies are higher in the South (e.g. Miethe et al. 1991), whereas others do not (Shihadeh and Flynn

[1]A few studies have used larger units of analysis, including a few county-level studies (Osgood 2000; Osgood and Chambers 2000; Worrall 2005).

1996; Stretesky et al. 2004). Other studies include a dummy variable for western states (Messner and Sampson 1991; Sampson and Cohen 1988), usually finding that robberies are higher in these states. A few studies include multiple regions (e.g. Baumer et al. 1998). Based on the widely known individual-level correlation between age and crime, most studies of robbery include some measure of the young population in a city, usually young males. Despite the theoretical rationale for including this measure, most studies find no relationship between the age structure of the city and robbery rates. In addition, consistent with Blau and Blau's (1982) arguments about the crime producing effects of income inequality, a few studies include measures of income inequality, particularly across race (e.g. Kubrin et al. 2006). Similarly, a few studies have also included a measure of residential instability (percent that moved in the last 5 years), based on the social disorganization perspective (e.g. Miethe et al. 1991). Thus, there appears to be a relatively standard set of factors included in most studies of robbery. Yet, with the exception of indices of disadvantage or deprivation, the relationship of individual covariates to robbery tends to vary depending on the sample and model specification.

A second category of studies, beginning with Wilson and Boland (1978), examines the deterrent effects of policing on robbery. Wilson and Boland (1978) argue that aggressive policing, or what we call "proactive" policing, is likely to reduce robbery in cities. Sampson and Cohen (1988) further develop this core idea, suggesting that the deterrent effect of proactive policing might emerge through two distinct processes. The first is by increasing the actual risk of arrest. "By stopping, questioning, and otherwise closely observing citizens, especially suspicious ones, the police are more likely to find fugitives, detect contraband (such as stolen property or concealed weapons), and apprehend persons fleeing from the scene of a crime" (Wilson and Boland 1978, p. 373). Proactive policing may also reduce robbery by increasing the perceived probability of arrest. Visible police enforcement of less serious offenses may cause potential offenders to believe their likelihood of apprehension has increased, in line with deterrence theory.[2]

Several studies have assessed the effect of aggressive or proactive policing on robbery rates,[3] and most have found a negative effect (but see Jacob and Rich 1980–1981). For example, Sampson and Cohen (1988) report that proactive policing directly reduces robbery rates in their sample of large U.S. cities circa 1980, and MacDonald (2002) detects similar effects for large U.S. cities in the mid-1990s. Recent research by Kubrin et al. (2006), using data from 2000 to 2003 on a sample of large cities, replicates this basic finding.

In sum, a fairly large body of literature on city-level robbery rates has accumulated. The results of this research are far from uniform, but they point to candidates for a baseline model of robbery rates (see also Land et al. 1990 for a similar set of predictors of variation in homicide). In addition, for the offense of robbery, policing style also appears to be a potentially important explanatory factor. However, unlike county-level studies (e.g. Baller et al. 2001; Messner et al. 1999) and the studies of smaller areal units (Cohen and Tita 1999; Kubrin and Weitzer 2003; Sampson and Morenoff 2004, 2006; Morenoff et al. 2001; Sampson et al. 1999), city-level research on robbery has largely neglected spatial dynamics. A rare exception is the study by Sampson (1986), which considers contextual effects on city-level robbery rates. Sampson includes a state-level measure of incarceration risk in his study of robbery and homicide in 171

[2]One concern that has been raised in deterrence research is the potential for artificially induced correlation due the common term (crime) in numerators (e.g. crime/population) and denominators (e.g. punishment/crime) of ratio variables, especially when there is error in the measurement of this variable (see e.g. Gibbs and Firebaugh 1990; Logan 1982). Recent research has shown that, even when measurement error is large as in the case of official crime measures, the practical impact is unlikely to influence substantive conclusions regarding deterrent effects (e.g. Levitt 1998; Pudney et al. 2000). This finding is consistent, more generally, with many of the concluding statements on the debate over the ratio variable problem (cf. Firebaugh 1988).

[3]A few studies have also examined the role of proactive or "broken windows" policing in the widely noted homicide decline in the 1990s. See Harcourt and Ludwig (2006), Kelling and Sousa (2001), Rosenfeld et al. (2005).

large U.S. cities and finds that higher risk of incarceration at the state-level reduces juvenile robbery offending. This finding points to potentially important spatial dependence in robbery rates at the level of cities, despite the general neglect of this possibility in the literature.

Potential Sources of Spatial Dependence of Violent Crime

Social scientists have long acknowledged the potential importance of spatial location. The advantages and, more often, disadvantages attributed to certain places and spaces have been the focus of numerous criminological and sociological studies. It has only been in recent years, however, that researchers have begun to recognize the value of explicitly examining spatial dynamics. As noted, most of the research on this topic has been limited to small areal units that are contiguous, such as neighborhood clusters and census tracts, or to larger units that are also contiguous, such as counties. Additionally, the scope of this research has been limited almost exclusively to the spatial patterning of homicides (Baller et al. 2001; Cohen and Tita 1999; Kubrin and Weitzer 2003; Morenoff et al. 2001; Sampson and Morenoff 2004).

Central to the application of spatial analysis of areal units is the idea that a place does not stand alone as “an island, entire of itself” but rather as “a part of the main.” Sampson, Morenoff and colleagues have outlined several theoretical reasons for anticipating spatial dependence (Sampson and Morenoff 2004; Morenoff et al. 2001). One such reason is that social phenomena may be susceptible to processes of diffusion. Recent empirical research supports this notion, demonstrating spatial dependence in homicide rates across both cities (Cork 1999) and counties (Baller et al. 2001) suggestive of diffusion processes for homicide. One possible reason for diffusion of various forms of criminal violence is the emergence of crack cocaine markets and the spread of youth gangs (Blumstein 1995; Cohen and Tita 1999). For example, Cork (1999) finds that crack cocaine use diffused across cities, followed by increases in both juvenile and adult homicides in those cities. Similarly, Baumer (1994) reports that increased crack cocaine use was associated with increases in robbery rates, net of other predictors (see also Baumer et al. 1998). Gang research also clearly shows that there is some migration of gang members, who are often involved in drug markets, from city to city (see Klein and Maxson 2006 for an overview). Thus, it is not unreasonable to expect that patterns of robbery would exhibit a spatial imprint reflecting the spread of drug markets. At the very least, this possibility should be investigated given the clear evidence of spatial dependence in homicides across expansive geographic areas.

Another reason to anticipate spatial dependence in areal analyses of social phenomena, including violent crime, is because the boundaries imposed by census geography do not necessarily coincide with the scale and operation of the underlying processes. Spatial models address the interdependence of place to partially accommodate the mismatch between the scale of units of observation and the scale of social processes. One specific type of “spatial mismatch” is likely to be particularly relevant to the analysis of violent crime across cities. Cities are effectively “nested” with the larger governmental units of states. Moreover, states are not arbitrary statistical aggregations but rather are jurisdictions that are vested with specific forms of authority (e.g., to set criminal statutes and penalties) and are delegated distinct responsibilities (e.g., for health, education, and social welfare). In addition, dramatic increases in prison populations in recent years have led to large numbers of ex-offenders. Given that most states constrain those on parole to remain within the state, it seems reasonable to assume that mobility of ex-offenders, who are likely to be at high risk for additional offending, will be more likely to be intra-state than interstate. Consequently, it seems reasonable to speculate that a city’s location in a given state might influence its robbery rate, independently of the city’s internal characteristics. Our modeling strategy enables us to evaluate the importance of the state context for city-level robbery rates.

Research Questions and Analytic Strategy

We address four overarching research questions. One, is there significant spatial autocorrelation in residuals of a standard baseline model of city-level robbery rates for a large sample of U.S. cites? Two, what are the consequences of any spatial autocorrelation for coefficients of covariates generated by means of least squares estimation? Three, how is spatial dependence best modeled, i.e., as a spatial lag or a spatial error process? Finally, what does a set of successive simplifications of the spatial weights matrix imply about the spatial scale of omitted determinants of robbery rates?

Our analyses proceed as follows. We begin by specifying a baseline model wherein (logged) robbery rate is a linear function of a comprehensive set of predictors informed by prior macro-level research on robbery and violent crime more generally. Following general practice, the initial baseline regression model is estimated using OLS. We then assess the OLS assumption that the errors are i.i.d. (independent and identically distributed) using the regression residuals and the Moran's I statistic with a spatial weights matrix identified by the distance between cities using the latitude and longitude coordinates of cities' geographic centers.[4]

Once residual spatial autocorrelation is observed, we initially follow the spatial econometric approach to determine the proper specification as a spatial error model or a spatial lag model. In spatial econometrics, the most common regression model specification captures the spatial autocorrelation in the error term: $y = X\beta + \varepsilon$, with $\varepsilon = \lambda W\varepsilon + \xi$ and where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$. The leading competing model, the spatial lag model (shown here as a mixed regressive, spatial autoregressive model), is formally: $y = \rho Wy + X\beta + \varepsilon$, where ρ is the spatial autoregressive parameter and Wy is the spatially lagged dependent variable for weights matrix W (Anselin 1988).[5] This distinction is important because a spatial error model points to the influence of unmeasured independent variables, while a spatial lag model also stipulates an additional effect of neighbors' robbery rates via a (spatially) lagged dependent variable. The spatial lag model is most compatible with common notions of diffusion and/or spillover processes because it implies an influence of neighbors' robbery rates

[4]Cliff and Ord ((1981); Anselin and Bera 1998) formally presented Moran's I as $I=\frac{N}{S_0}\left(\frac{e'We}{e'e}\right)$, where e is a vector of regression residuals, W is a spatial weights matrix, N is the number of observations, and S_0 is a standardization factor equal to the sum of the spatial weights. An alternative expression shows Moran's I to be the two-dimensional (i.e., spatial) analog of the coefficient of autocovariance, ρ, for univariate time series correlation. This can be seen by comparing $\widehat{\rho}=\frac{\sum(e_t \times e_{t-1})}{\sum e_t^2}$ to the alternative expression of $I=\frac{\sum_i\sum_j w_{ij}(e_i \times e_j)}{\sum_i e_i^2}$. The most common specification of the spatial weights matrix W is to link every unit i to every other unit j by the inverse of distance between i and j, thus the elements of W are $\frac{1}{d_{ij}}$. Generally the W matrix is then row-standardized to unity across rows. We use the Moran's I option in CrimeStat (Levine 2004) to calculate residual spatial autocorrelation under this specification.

[5]We initially fit spatial lag and spatial error regressions in GeoDa (Anselin et al. 2005) using a threshold distance-based weights matrix. The threshold distance function in GeoDa finds the global minimal distance between cities' geographic centers that will leave no city as an "island," unconnected to any other city. We then use SAS' PROC MIXED procedure with a spatial error covariance structure to replicate the spatial error model. In PROC MIXED, spatial autocorrelation is integrated into the general mixed model through a distance function in the error covariation. If we start by writing the general mixed model as $y = X\beta + Zu + e$, where everything is the same as in the general linear model except for the addition of the known design matrix, Z, and the vector of unknown random-effects parameters, u. Z can contain either continuous or dummy variables, just like X. The name "mixed model" comes from the fact that the model contains both fixed-effects parameters, β, and random-effects parameters, u. If we assume that u and e are normally distributed with $E\begin{bmatrix} u \\ e \end{bmatrix}=\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ and $VAR\begin{bmatrix} u \\ e \end{bmatrix}=\begin{bmatrix} G & 0 \\ 0 & R \end{bmatrix}$, the variance of y is $V = ZGZ' + R$ and V can be modeled by specifying the random-effects design matrix Z and by specifying covariance structures for G and R (Littel et al. 2006, p. 438ff.). As with repeated measures, the spatial mixed model assumes that the errors (the elements of e) are correlated and the form of the spatial dependence can be reflected in R. In the general mixed model the covariance structure of R can be defined by letting $Var(e_i)=\sigma_i^2$ and $Cov(-e_i,e_j) = \sigma_{ij}$. In the spatial mixed model the covariance is assumed to be a function of the distance (d_{ij}) between the locations s_i and s_j, thus the resulting models have the general form: $Cov(e_i,e_j) = \sigma^2[f(d_{ij})]$. The MIXED procedure requires that observations be uniquely identified with a spatial coordinate and that the spatial (error) process that generated the data satisfy certain stationarity conditions, such as equal variance among the observations. Although the MIXED procedure in SAS supports many spatial functions, we use the power function $f\, d_{ij} = \rho^{d_{ij}}$, where d_{ij} is distance between cities.

that is not simply an artifact of unmeasured independent variables. Spatial lag and spatial error are alternative forms of spatial dependence, with the spatial error model subsumed by the spatial lag model, though in a non-nested form. An important distinction is that least squares estimation in the presence of spatial error dependence is inefficient; the parameter estimates, $\hat{\beta}$, may be unbiased (conditional on the effect of the omitted variable(s) on the correlational structure of the covariates), but the variance estimates are known to be biased and may lead to incorrect inference. On the other hand, if the OLS estimator used when the true model is a spatial lag, the omitted spatial lag term guarantees biased and inconsistent estimates of β. This is clearly seen in the reduced form of the spatial lag model as the presence of ρWy implies a fully interactive model that alters the interpretation of the $\hat{\beta}$ coefficients (Baller et al. 2001, p. 571; Anselin and Bera 1998, pp. 246–249; Case 1991, p. 956).

An equally important aspect of spatial modeling is the representation of spatial structure via the spatial weights matrix. The spatial weights matrix defines the strength of the potential interaction between locations. The determination of the proper specification for the elements of a spatial weights matrix is considered one of the most difficult and controversial methodological issues in spatial data analysis (Bao 2001). Yet it has been observed that while most spatial analysts recognize that the spatial weights matrix is supposed to be a theoretical conceptualization of the structure of spatial dependence, more often than not the choice of the spatial weights matrix is at best that which is empirically convenient (Getis and Aldstadt 2004).

Thus, informed by our discussion of potential sources of spatial dependence of violent crime in section "Potential Sources of Spatial Dependence of Violent Crime", we impose two forms of local dependence in the distance-based spatial weights matrix to further elucidate the contours of the geography of spatial dependence in city robbery rates: (1) an intermediary parameterization in which residuals are a function of distance but only among cities within the same state (e.g., only cities in California are allowed to influence other cities in California but that influence is a function of distance); and (2) residuals are correlated within a state regardless of distance between cities in that state.

In summary, we have specified a hierarchy of distance-based spatial weights matrices wherein the distance within-states matrix is a simplification of the full distance spatial weights matrix and the within-states regardless of distance matrix is a simplification of the distance within-states matrix. With each simplification we gain parsimony in terms of the unique elements of the spatial weights matrix. We fit five regression models (OLS, spatial lag, spatial error, and the two alternative specifications of the spatial weights matrix) and identify the best fitting model. In addition to Moran's I as a model criticism tool, we assess the goodness-of-fit and model selection of spatial process models by comparing the maximized log-likelihood or an adjusted form to take into account the number of parameters in the model. The latter statistics, known as information criteria, improve (decline) as R^2 increases, but, all else equal, degrade as the model size increases. We report *BIC*, also known as the *Schwarz Criterion*, which poses a heavier penalty for model complexity (degrees of freedom lost), than some of the other popular *IC* measures, most notably, *AIC*. *BIC* is defined as $-2LL + d \times \log(N)$, where LL is the maximum value of the log-likelihood, d is the dimension of the model, and $\log(N)$ is the natural log of the number of observations. The preferred model is the one that yields the *BIC* with the smallest value.

Data

The Sample and Dependent Variable

The units of analysis for the research are cities with populations of 25,000 or more in 2000. To generate the sample, we initially collected data on robbery "offenses known" for all cities satisfying the population size criterion that participated in the *Uniform Crime Reporting* (UCR) program at any time during the 4-year period: 2000–2003.[6] The UCR counts of robberies known to police, along with the corresponding population totals, were taken from files distributed by ICPSR for all years except 2003.[7] The 2003 UCR data were taken from the FBI's website (Table 8, http://www.fbi.gov/ucr/03cius.htm).

Robbery rates (per 100,000 population) were computed in the conventional manner for each year with available data using the robbery counts and population totals from the UCR. To reduce the likelihood that reporting error might produce unstable estimates, especially for relatively small cities, we imposed the selection criterion that a city must have at least 2 years of data to be included in the analyses and smoothed the data over multiple years. If a city reported for all years in the interval, the robbery rate is based on the 4-year total. If the city reported for three of the 4 years, the robbery rate reflects those 3 years, and so on. The smoothed robbery rates were converted into natural logarithms to reduce right skew. After listwise deletion of cases due to missing data on the independent variables, a total of 1,056 cities are available for the analysis.

Independent Variables

Our baseline model of predictors is informed by prior macro-level research on robbery and violent crime more generally. We collected data from the 2000 Census on the following characteristics of cities: population size (logged); racial composition (percent population non-Hispanic black); poverty (percent of the population below the poverty line); percentage of the population age 15 and over that is divorced; unemployment (percent of the population age 16 and over who are unemployed); education (percent of the population age 18 and over who have graduated from high school); female-headed households (percent households with children under age 18 that have a female householder and no husband present); residential instability (percent of the population age 5 and over who have moved into a different house within the last 5 years); and percent young males (percent of the population that is male aged 15–24). These socio-demographic characteristics of cities, as well as the latitude and longitude of each city, were extracted from the SF3 Census 2000 files using the state-place summary level of aggregation.[8]

To reduce collinearity, we followed standard procedures and conducted principal components analysis on variables that potentially reflect a common, underlying dimension: residential instability, percent young males, percent divorced, percent poverty, percent unemployed, percent high school graduates, percent female-headed households, median family income, and percent non-Hispanic black. Consistent with prior violent crime research (Land et al. 1990; Parker and McCall 1999), a "resource deprivation" factor emerged from the results. The following variables loaded strongly on the resource deprivation factor (factor loadings are in parenthesis): percent poverty (.87), median family income (−.87), percent unemployed (.85), percent female-headed households (.87), and percent high school graduate (−.84). With an

[6]Cities in Florida and Illinois did not report the arrest information used to generate the proactive policing measure to the UCR and are therefore excluded from the analyses. Additionally, cities in Alaska and Hawaii had to be excluded because the distance measures would have been unduly influenced by the fact that they are not contiguous with the rest of the states.

[7]The source is the National Archive of Criminal Justice Data located on the Inter-University Consortium for Political and Social Research (ICPSR) website (http://www.icpsr.umich.edu/NACJD/archive.html, as compiled in studies #9028 (1996–1997), #2904 (1998), #3158 (1999), #3447 (2000), #3723 (2001), and #4008 (2002).

[8]Census designated geographic entities do not recognize the popular conception of "cities" per se. Rather, the Census Bureau designates "places," assigning them five-digit FIPS place codes, including "incorporated places" that generally match the entities we think of as cities. We use this summary level of aggregation to extract the socio-demographic characteristics that we link to UCR ORI robbery rates. In addition, the Census Bureau assigns a latitude and longitude (in decimal degrees) to an "internal point" in each designated geographic entity. A single point is identified for each entity that (usually) represents the geographic center of that entity. The source for the Census data and documentation is: Census 2000 Summary File 3 [United States]/prepared by the U.S. Census Bureau, 2002; Census 2000 Summary File 3 Technical Documentation/prepared by the U.S. Census Bureau, 2002.

eigenvalue of 3.7, this factor accounted for about 74% of the variation in the construct. We computed the resource deprivation index using the corresponding factor scores. The socio-demographic characteristics not contained in the composite index are included in the regression models as separate covariates.

We also include an indicator of proactive policing in our models. Following Sampson and Cohen (1988), and Kubrin et al. (2006), proactive policing is operationalized with reference to the vigorous enforcement of relatively common offenses. The specific measure is the sum of the number of arrests for driving under the influence (DUI) and disorderly conduct, divided by the number of sworn police officers. We computed this ratio for each year during the 2000–2003 period and averaged the values for years with non-missing data, imposing the requirement of a minimum of 2 years of data for inclusion. We also logged this variable to correct for skewness. The FBI provided the arrest and police employee data for the proactive policing measure in a personal communication.[9] Additionally, following some prior research in this area suggesting regional differences in robbery rates (e.g. Messner and Sampson 1991; Sampson 1986; Sampson and Cohen 1988), our models include a dummy variable indicating location in the Western region of the U.S.[10] Descriptive measures of our variables are shown in Table 1.

Results

Our analyses begin with a classical linear regression of robbery rates on the hypothesized determinants. The results of the OLS estimation are provided under Model 1 in Table 2. The pattern of coefficients is generally in accord with prior research and criminological theory. Population size, percent divorced, resource deprivation, the relative size of the Non-Hispanic Black population, and Western region exhibit significant positive effects on robbery rates. The measure of age structure (percent young males) and the indicator of proactive policing are negative and statistically significant; this is the expected direction of effect for proactive policing, but not for age structure.[11] The measure of residential instability is not related to robbery rates. Overall, the regression model has reasonably impressive explanatory power, as reflected in the R^2 of 0.69.[12]

The residual spatial dependence in Model 1 is shown in the Moran's I Scatterplot in Panel A of Fig. 1. The observed value, $I = 0.089$, relative to its expectation (−0.0009) and estimated standard error (0.0071), produces a test statistic signaling significant correlation among neighboring OLS residuals. This is confirmed visually by the positive slope of the scatterplot.[13]

With strong evidence of residual spatial autocorrelation based on Moran's I we can conclude that Model 1 is misspecified, but we must determine the extent of the damage. Are the estimated regression coefficients, $\hat{\beta}$, given in Model 1 misleading and/or misinterpreted; or is the effect

[9] We are grateful to Debra K. Mack, Chief of Programs Support Section of the FBI's Criminal Justice Information Services Division, for providing the arrest and employee data and for clarification of these data.

[10] Some other recent city-level research has found that a dummy variable for cities in southern states is unrelated to robbery rates (e.g. Shihadeh and Flynn 1996; Stretesky et al. 2004).

[11] The interpretation of the negative coefficient for proactive policing is problematic given potential endogeneity. High robbery rates may inhibit the capacity of police agencies to engage in proactive policing. However, partitioning potential reciprocal effects for proactive policing and robbery rates is not central to the purposes of the present analysis.

[12] Table 2 also reports *BIC*. We calculate *BIC* with *d* (the dimension of the model) as the rank of the **X** matrix + the effective number of estimated covariance parameters. Therefore, $d = 10$ (8 covariates + intercept + error variance) and OLS $BIC = 1949.5$.

[13] Based on the observed I, the expectation of I, and the standard deviation generated by the randomization, the test statistic is $Z_I = \frac{I - E(I)}{sd(I)} = \frac{0.0886 - (-0.0009)}{0.0071} = 12.61$, with $p \leq 0.001$. The Moran Scatterplot shown in Fig. 1 is produced in GeoDa based on a distance threshold spatial weights matrix. We also calculate the residual Moran's I from Model 1 in CrimeStat utilizing a full distance weights matrix (see fn. 5). The result is almost identical: $I = 0.087$ and $Z_I = 15.79$.

of the spatial autocorrelation confined to the variance estimates of Model 1? We pursue this determination by fitting spatial lag and spatial error models using a conventional distance-based spatial weights matrix. In addition to standard model selection statistics (BIC_{LAG} = 1913.1; BIC_{ERROR} =1874.0), regression diagnostics based on the application of the Lagrange Multiplier (*LM*) principle have been developed expressly for spatial econometric regressions (Anselin 1988; Anselin and Rey 1991; Anselin et al. 1996). These statistics unambiguously point to a spatial error model as the preferred model.[14] At first blush, this would appear to be good news for previous research that has reported least squares estimates of the effects of the baseline predictors in city-level analyses because least squares estimation in the presence of spatial error dependence is inefficient, but the parameter estimates $\hat{\beta}$ may still be unbiased.[15]

We report the spatial error model as Model 2 in Table 1 and the residual Moran's I Scatterplot in Panel B of Fig. 1. The residual Moran's I ($I = 0.0002$, $p > 0.5$) and flat scatterplot confirm that the spatial error model has eliminated spatially correlated error. In other words, the residuals of neighboring cities are no more alike than the residuals of randomly paired cities. The spatial dependence has been captured and quantified in the spatial error covariance parameter. Also as expected, the unstandardized and standardized (shown in square brackets in Table 2) coefficients in Model 2 remain similar to the OLS coefficients. It is important to note however that with unbiased variance estimates we see two changes in inference: age structure and Western region are no longer significantly related to robbery rates.

If our sole objective were unbiased estimation and inference from the baseline model, we might stop here. If we were to do so, we would be tempted to interpret the residual spatial dependence, now accounted for in the spatial error model, as the spatial imprint of proximity: nearer cities share an ecological context, not all of which is observable or specified in our baseline model. We might also pursue observable but omitted city-level covariates as potential vectors of transmission of the spatial dependence via the techniques of Exploratory Spatial Data Analysis (cf. Messner et al. 1999). Instead, we impose local structures in the spatial weights matrix as an alternative means of exploring the structure of error covariance. Spatial data analysis is only as informative as its neighborhood structure allows it to be. The form of that structure is more often than not chosen as a matter of convenience or by constraints imposed by software packages rather than substantive reasoning. By considering competing structures of spatial dependence we produce an additional example of biased inference, while extracting additional insight to the structure of omitted covariates of violent crime.

In Table 2, Model 3 gives the estimated regression coefficients and model fit from our intermediary parameterization in which residuals are a function of distance but only among cities in a state. Specifically, the spatial weights matrix used in Model 3 includes elements of inverse distance between cities within states, but matrix elements are set to zero when cities are linked to cities from another state. Model 4 accounts for residual correlation by simply nesting cities within states. In Model 4, residuals are correlated within states regardless of distance between cities, with the error covariance between cities of different states set to zero.

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[14]Formally, the LM statistic against spatial error autocorrelation takes the form $LME = [e'We/s^2]^2/T$, with e as a vector of OLS residuals, s^2 as its estimated standard error, and $T = [tr(W + W')W]$. This statistic, *LME*, is asymptotically distributed as $\chi^2(1)$ under the null. The *LM* statistic for spatial lag dependence is somewhat more complex: $LML = [e'Wy/s^2]^2/[(WX\beta)'M(WX\beta)/s^2 + T]$, with $M = I - X(X'X)^{-1}X'$, β as the OLS estimate, and T and the distributional form of the statistic as before. Anselin et al. (1996) further developed a robust form of the *LM* statistics wherein the robust *LME* is robust to the presence of spatial lag when quantifying spatial error, while the robust *LML* is robust to the presence of spatial error. In this application, $LML = 45.76$ and $LML_{Robust} = 4.35$; $LME = 154.96$ and $LME_{Robust} = 113.31$. Although LML_{Robust} remains statistically significant at $p < 0.04$, given the relatively large N, the robust quantification of spatial error that is over 26 times larger than the robust quantification of spatial lag, and the statistically significant residual spatial autocorrelation remaining in the spatial lag model ($I = 0.05$, $Z_I = 7.44$, $p < 0.001$), the evidence points unequivocally to a spatial error model as the preferred spatial econometric model.

[15]Given the strong preference for spatial error model estimation over the spatial lag model, we do not report parameter estimates from the spatial lag model among the models in Table 2 because our diagnostics confirm that this model is misspecified.

Note that if the error covariance between all cities is set to zero, we again have the classical linear regression of Model 1.

The *BIC* statistics reported under the models show the successive improvement in model fit (shown in the reduced values of *BIC*) as we move away from distance-based scaling of the error covariance. Model 3 (*BIC* = 1840.9) shows substantial improvement over Model 2, but Model 4 (*BIC* = 1808.9) offers a far better fit still. The residual spatial autocorrelation that was eliminated by the full distance-based spatial weights matrix in Model 2 remains unaffected by simplifications of the spatial weights specifications in Models 3 and 4 but the gains in parsimony are reflected in the declining values of *BIC*. Said differently, distance-based spatial weights in Models 2 and 3 overparameterize the source of residual spatial dependence; and in doing so, the estimated effect of region (West) is unduly suppressed.

We have already shown that unmodeled spatial dependence leads to incorrect inference concerning the effect of age structure (percent young males) on city-level robbery rates. With distance based spatial dependence, we would extend this conclusion to the effect of region (West). Our pursuit of alternative structures of spatial dependence, leading to a simple nesting of cities within states, reveals that the expected values of robbery rates in the West are actually lower than those in other regions, net of the effect of the other covariates. If within-state correlation is not purged from the regression residuals, analysts conclude that robbery rates in the West are higher than in other regions, after adjusting for other model covariates. When we recall that OLS estimation in presence of spatial dependence may violate the assumption that the errors of prediction and an independent variable are uncorrelated, and that that assumption will be violated if an excluded variable is highly correlated both with the dependent variable and with one (or more) independent variable, we can understand why the effect of region is sensitive to our efforts to purge spatial dependence and the structure in which we accomplish this. Our preference for Model 4 over Model 3 suggests that proximity per se does not matter: the residuals of nearer cities within states are no more alike than those paired at random within states. If states structure the residual spatial dependence, then omitted variable bias is likely to be due to excluded state-level variables. Region is a closer proxy of state-level dynamics than any of the city-level covariates in our regression model, therefore we should expect that region will respond more abruptly structures of spatial dependence, particularly state-level structures.

It is important to recognize that spatial regression models are designed to yield indirect evidence of spatial influence in cross-sectional data and provide instrumental variable (IV) estimation of that influence so that inference from the observable structure is unbiased. However, dependence ultimately requires “vectors of transmission,” i.e., identifiable mechanisms through which events in a given place at a given time influence events in another place at a later time. Spatial error (and spatial lag) models, as such, are not able to discover these mechanisms. Rather, they depict a spatial imprint at a given instant of time that would be expected to emerge if the phenomenon under investigation were to be characterized by one or the other process. The more pressing task is to identify the relevant array of features that comprise the ecological context, include measures of them in the systematic component of the statistical model, and ultimately theorize about the processes that link these features to levels of the dependent variable.

Although our alternative specifications of the spatial error model locate correlated error within the geography of states, rather than the proximity of cities, the substantive gain of this statistical modeling will only be fully realized once the observable vectors of transmission have been identified. Metaphorically, we have not yet found the house, but we think we know what street it is on. To illustrate the way in which further inquiry might build upon our analyses, we have considered a number of state-level covariates as “geopolitical drivers” of the state-level clustering of residuals. These include two indicators of the political environment—

politicization of judge selection and government ideology—and two indicators of incarceration practices—total prisoners admitted per index crimes and the ratio of the number of prisoners in custody to total state population (averaged over the 1999–2002 period). Of these four state-level measures, only the indicator of government ideology yields "value added" in explaining intercity variation in robbery rates. This indicator is an index that combines ideology scores for five state political actors including the governor and the two major parties in each state legislature. The index ranges from 0 for the most conservative state governments to 100 for the most liberal. A complete description of this variable can be found in Berry et al. (1998).[16]

Model 5 of Table 2 demonstrates the utility of this search for state-level covariates. The addition of government ideology (scored in the direction of government liberalism) improves model fit (*BIC* = 1801.5), and the effect is positive and statistically significant. Put another way, city-level robbery rates are *lower* in more conservative states, adjusting for a wide array of city-level characteristics; though the standardized effect is among the smallest in our model. Substantively, this might be interpreted as support for the deterrence perspective, given that, ceteris paribus, more conservative governments can be expected to enact "law and order" policies that would likely focus on increased use of policing and stiffer criminal penalties. Such a conclusion is tempered, however, by the fact that neither indicator of state punishment practices included in the current study is significantly related to city-level robbery rates, nor did either substantially reduce the within state residual correlation.[17] Although it is premature to suggest any definitive conclusions without more complete models of state-level predictors, we appear to be moving in the right direction by theorizing about the state-level ecological context of violent crime. Ultimately, the goal is to determine a set of theoretically important predictors of crime, which reduce the city-level residual correlation to zero, without the need to absorb that residual correlation in spatial autocorrelation coefficient.

Summary and Conclusions

This research has examined spatial dependence in city-level robbery rates. We have addressed four overarching questions. One, is there significant spatial autocorrelation in residuals of the standard baseline model of city-level robbery rates for a large sample of U.S. cites? Two, if spatial autocorrelation is detected, are the coefficients for covariates generated by means of least squares estimation biased? Three, how is spatial dependence best modeled? Finally, what does the pattern of spatial dependence imply about omitted determinants of robbery rates? Following estimation of several relevant models using data on cities with 25,000 or more residents circa 2000, we arrive at the following conclusions.

First, the implicit assumption in previous studies that cities can be regarded as independent observations in analyses of robbery rates, or violent crime more generally, should not be accepted at face value. We find statistically significant residual spatial autocorrelation. Thus, it seems likely that prior city-level models of robbery rates have been misspecified because they have failed to account for correlated error.

Second, we find that spatial dependence is best modeled as a spatial error rather than spatial lag process, and that the effects of spatial interdependence are manifested in inefficient

[16]The indicator of politicization of judge selection is a scale from 1 to 4 based on how local judges are selected. The scale has a value of 1 for appointed judges; 2 for judges that are initially appointed and then renewed through popular election (Missouri plan); 3 for nonpartisan popular elections; and 4 for partisan popular elections. The source of this data is *The Book of the States* (Council of State Governments 2000). We are grateful to Paige Harrison, Bureau of Justice Statistics, for providing the incarceration data in a personal communication.

[17]We note that this finding is the opposite to what one might predict from the standpoint of recent research on social support or institutional anomie theory. These perspectives imply that conservative policies leave citizens more susceptible to the vicissitudes of the market and thus increase crime (see e.g. Colvin et al. 2002; Messner and Rosenfeld 1997; Savolainen 2000).

estimation, that is, biased variance estimates. Therefore, determination of significance of predictors may be affected, but, conditional on model specification and the effect of omitted variable bias on the correlational structure of model covariates, parameter estimates may be unbiased. Estimation of the effect of West region, which turns from positive to negative, and percent young males in the spatial error models of Table 2 provide evidence that conclusions reached by prior research under OLS estimation may be influenced by inefficient variance estimates and omitted variable bias.

Finally, probing into the residual spatial autocorrelation indicates that the most appropriate weights matrix for the spatial error models is one that treats cities within states as neighbors, irrespective of the distance between cities. This illustrates the promise of investigating the structures of correlated error as a means of theory construction.

Although the precise nature of omitted variables is indeterminant, the possibilities are intriguing. These variables might encompass genuine “contextual” factors, i.e., properties that are intrinsic to states and that have no strict analogues at the city level. Such contextual properties would include features of the legal environment and criminal justice system that are determined at the state-level and that accordingly exhibit no variation across cities within states. Alternatively, the omitted variables might reflect social conditions that can in principle be conceptualized as city-level properties that for some reason exhibit greater homogeneity within states than between states, but that are not otherwise linked with physical distance. Further inquiry into such possibilities is a promising topic for future macro-criminological research.

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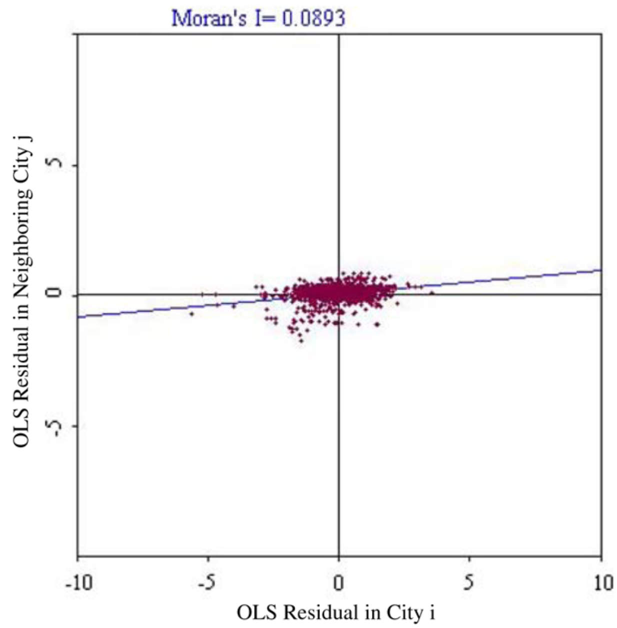
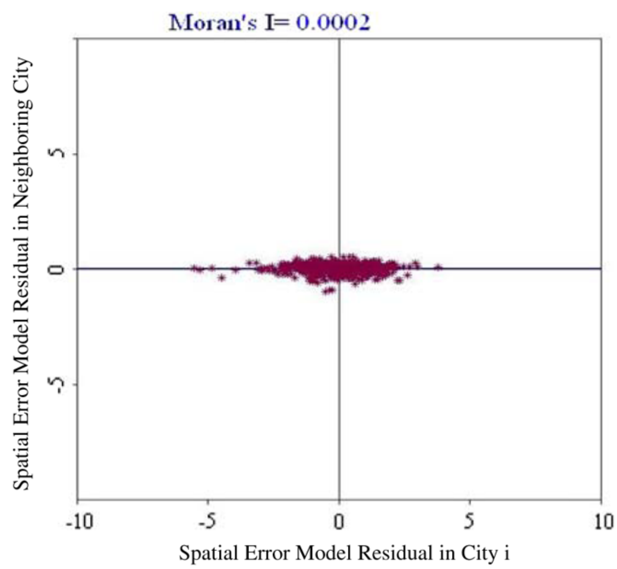


Panel A. Moran's I (I=0.089, p<0.001) Scatterplot of Model 1 (OLS) Residuals



Panel B. Moran's I (I=0.0002, p<0.5) Scatterplot of Model 2 (Spatial Error) Residuals

Fig. 1.

(Panel **A**) Moran's I (I = 0.089, p <0.001) Scatterplot of Model 1 (OLS) residuals. (Panel **B**) Moran's I (I = 0.0002, p <0.5) Scatterplot of Model 2 (Spatial Error) residuals

Table 1

Descriptive statistics (N = 1056)

Variable	Mean	Standard deviation	Minimum	Maximum
(log) Robbery rate	4.41	1.06	0.51	7.16
(log) Proactive policing	1.17	0.73	−3.46	4.29
(log) Population	10.96	0.77	10.13	15.90
Percent divorced	9.84	2.54	2.45	17.70
Resource deprivation index	0.00	1.00	−2.52	3.75
Percent young males	7.15	3.54	1.33	35.26
Percent moved	48.77	9.29	25.19	81.61
Percent black	10.59	14.75	0	87.47
Western dummy variable	0.29	0.45	0	1
Government liberalism	50.94	1.06	0.51	7.16

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Table 2

Ols and spatial error regression models (N = 1056)

	Model 1 OLS	Model 2 Spatial error full distance	Model 3 Spatial error distance within state	Model 4 Spatial error within state Model I	Model 5 Spatial error within state Model II
(log) Population	.326* (.026) [.237]	.297* (.024) [.216]	.301* (.024) [.219]	.328* (.024) [.238]	.333* (.024) [.242]
Percent divorced	.069* (.009) [.165]	.087* (.009) [.208]	.086* (.009) [.206]	.104* (.009) [.249]	.104* (.009) [.249]
Resource deprivation index	.507* (.025) [.478]	.493* (.026) [.465]	.491* (.026) [.463]	.487* (.024) [.459]	.483* (.024) [.456]
Percent black	.020* (.002) [.278]	.017* (.002) [.237]	.017* (.002) [.237]	.016* (.002) [.223]	.016* (.002) [.223]
Percent young males	−.017* (.008) [−.057]	−.013 (.008) [−.043]	−.014 (.008) [−.047]	−.002 (.008) [−.007]	−.001 (.008) [−.003]
Percent moved	−.0003 (.003) [−.003]	.003 (.003) [.026]	.003 (.003) [.026]	.001 (.003) [.009]	.001 (.003) [.009]
(log) Proactive policing	−.117* (.028) [−.081]	−.068* (.029) [−.047]	−.066* (.029 [−.045]	−.124* (.030) [−.085]	−.115* (.030) [−.079]
West Dummy variable	.144* (.046) [.061]	−.016 (.057) [−.007]	−.015 (.057) [−.006]	−.238* (.119) [−.101]	−.181 (.108) [−.077]
Intercept	.176 (.288)	.093 (.286)	.060 (.287)	−.335 (.298)	−.675* (.312)
Government liberalism	–	–	–	–	.007* (.002) [.007]
R^2	0.69	–	–	–	–
Moran’s I	0.089	0.000	0.000	0.000	0.000
BIC	1949.5	1874.0	1840.9	1808.9	1801.5

Standard errors are given in parentheses and standardized coefficients in brackets

* Statistically significant at the .05 level, two-tailed test